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MODEL FOR INDIRECT MEASUREMENTS OF LD - STEELMAKING PROCESS

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This paper describes a statistical approach to modelling the LD-steelmaking process. The steelmaking process belongs to very complicated metallurgical processes, in which the measurement of process variables is very difficult and economically challenging. Among these variables are mostly the concentration of carbon in hot metal and the temperature of bath. Both of them are very important for predicting the end of blowing. We can obtain an appropriate prediction by using a simulation model of the technological process. We recognize several approaches to making simulation models and bave chosen the statistical approach which counts selected process variables from regression equation step by step. An advantage of using a regression model is that we can eliminate interruption of blowing.

Key words: *LD-process, indirect measurements, regression analysis, predictions*

Model neizravnog mjerenja LD-postupka dobivanja čelika. Rad obrađuje statistički pristup dobivanju čelika LD-postupkom. Postupak dobivanja čerika se ubraja u vrlo komplicirane metalurške procese u kojima je mjerenje varijabli vrlo teško i izazovno u gospodarskom pogledu. Među tim varijablama najčešće nalazimo koncentraciju ugljika u vrućem metalu i temperaturu kupke. Oboje su važni za predviđanje kraja upuhivanja. Adekvatnu prognozu možemo dobiti uporabom modela simulacije tehnološkog procesa. Ima više pristupa izradi modela simulacija, a mi smo odabrali statistički model koji prebrojava odabrane procesne varijable korak po korak iz regresivnih jednadžbi. Korist korištenja regresivnog modela je u tome da možemo eliminirati prekidanje upuhivanja.

Ključne riječi: *LD-postupak, neposredno mjerenje, regresivna analiza, predviđanja*

INTRODUCTION

At the present time the production of steel in LD - converters belongs to the most widely used technology in manufactu-ring pig iron. The steelmaking process belongs to very complicated metallurgical processes. Because of high pro-duction costs, which are closely tied to the interruption of the melting process with an early check, the tendency is to minimize these costs. It would be an advantage to do away with the early check.

CHARACTERISTIC OF THE TECHNOLOGICAL PROCESS

The process of making the steel malleable in LD-converters consists in pouring pig iron into the converter, and adding slag additions (lime, dolomite lime, magnesite), scrap, and iron ore. An oxygen jet blows pure oxygen into the converter, which causes oxidation of the additives of the iron melt. These reactions are exothermic, no other source of energy is needed to raise the bath temperature [1].

The exothermic reactions heat is used to melt down scrap, lime, and other slag additions. The chemical reactions of blown oxygen give rise to the following oxidation reactions:

- carbon oxidation;
- manganese oxidation;
- silicon oxidation;
- phosphorus oxidation;
- sulphur oxidation.

INDIRECT MEASUREMENT

Indirect measurement is one of the ways in which, by means of some measured quantities, we can determine another quantity.

The possibilities of indirect measurement are as follows:

- by means of a sounder (sublanze);
- from gas analysis;
- by means of prediction model.

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Indirect measurement by means of sounder

At present, sounders are being widely used for the determination of hard-to-measure quantities, which in a very small time interval are capable of evaluating for example the temperature of metal or the percentage content of carbon in the metal. A disadvantage of the sounder is that it can only be used once. In the process of temperature sampling it would take 15 to 20 pieces of sounders for every minute of the process of malleableazing which eventually represents a considerable cost considering the high price of the sounder.

Indirect measurement from analysis of converter gas

A more frequently used method of indirect measurement is one based upon analysis of converter gas. The rate of decarbonization is calculated from CO and CO_2 concentrations in converter gas and the volume of converter gas flow (1).

$$\frac{dC}{dt} = k \cdot V_{CG} \cdot \left(X_{CO} + X_{CO_2} \right) \tag{1}$$

where

k is a constant,
V_{CG} is the volume of converter gas,
X_{CO} is the concentration of CO in converter gas, and
X_{CO_2} is the concentration of CO_2 in converter gas.

Indirect measurement by means of prediction model

We chose a different approach, in which we considered dynamic quantities of the converter process, which were measured during the melt process. The emphasis was on the quantities measured from converter gas as in the previous case and the speed of decarbonization was computed not from the CO and CO_2 content but the oxygen percentage content was predicted at each time step by using a difference equation.

MODEL FOR PREDICTION OF CARBON CONTENT AND BATH TEMPERATURE

When determining the parameters for prediction model we used the dynamic parameters, which are measured during melting. Among these dynamic parameters belong:

- CO content in converter gas;
- CO_2 content in converter gas;
- temperature of converter gas;
- pressure of converter gas;
- lance height;
- volume flow of oxygen.

Basic prediction model

We decided for the prediction of carbon content and bath temperature, since these parameters are important for tapping steel. We based our analysis on regression, where the equation for linear multi-regression has the following form [2]:

$$Y = a_0 + \sum_{i=1}^{n} a_i \cdot x_i \tag{2}$$

In our case the prediction model was established based on two equations in which, at each time step, the values of dependent variables Y_l are calculated iteratively.

$$Y_l(k+1) = a_{l0} + \sum_{i=1}^{n} a_{li} \cdot x_{li}(k) + \sum_{j=1}^{m} a_{lj} \cdot v_{lj}(k) \tag{3}$$

where

$Y_l(k+1)$ is the dependent output variable at (k+1)th step,
$x_{li}(k)$ is the independent input variable at kth step,
$v_{li}(k)$ is the control variable, and
a_{li} is the regression parameter.

The time step Δt for the prediction is given by the following equation (4).

$$\Delta t = t_{k+1} - t_k \tag{4}$$

The calculation of regression parameters a_i was performed using the least squares method. We calculated the sum of deviations F at each time step and by its minimi-zation we obtained a system of equations, from which we calculated the vector of parameters a_i.

$$F = \sum_{k=1}^{p} \left[\left(a_0 + \sum a_i \cdot x_i(k) \right) - Y_k(k+1) \right]^2 \tag{5}$$

$$\frac{\partial F}{\partial a_i} = 0 \tag{6}$$

We tested several variants of the prediction model. In the first step we wanted to emphasize the importance of the time step Δt for prediction.

The prediction model was compared to real melting and relative deviation ε in % was specified (7).

$$\varepsilon = \frac{\left| Y_{meltage} - Y_{model} \right|}{Y_{meltage}} \cdot 100 \ [\%] \tag{7}$$

where

ε is the relative deviation,
$Y_{melting}$ is the value in melting,
Y_{model} is the value in model.

Data, which we had at our disposal were measured in four-seconds intervals. In Table 1. the results of three variants by various time step Δt are presented. We can see that best resuls are with least time step [3].

Table 1. **Relative deviations basic prediction model for time step Δt**
Tablica 1. **Osnovni model predviđanja relativnog odstupanja za vremenski korak Δt**

No.of melt.*	**58246**	**58247**	**58249**	**58250**	**58251**	**58253**	**58254**	**58255**	**58257**
Δt = 60 s									
De.of car.**	61	19	135	100	2	1	84	44	11
De.of te.***	0.394	0.008	0.245	0.198	0.027	0.029	0.105	0.281	0.446
Δt = 30 s									
De.of car.**	145	67	43	7	19	336	135	31	37
De.of te.***	0.685	0.098	0.096	0.001	0.148	0.921	0.257	0.041	0.111
Δt = 4 s									
De.of car.**	55	92	302	69	68	67	78	46	20
De.of te.***	0.244	0.471	0.151	0.825	0.078	0.070	0.155	0.132	0.084

* Number of melting, ** Deviation of carbon [%], *** Deviation of temperature [%]

Other variants of the prediction model are presented in the following section.

a) Prediction model for carbon contents and bath temperature based on CO content, CO_2 content, pressure, temperature of converter gas, and control variables.

$$\begin{aligned} \%\mathrm{C}(k+1) &= a_0 + a_1 P(k) + a_2 T_{CG}(k) + \\ &+ a_3 \%\mathrm{CO}(k) + a_4 \%\mathrm{CO}_2(k) + a_5 lh(k) + a_6 V_{O_2}(k) \end{aligned} \tag{8}$$

$$\begin{aligned} \%T(k+1) &= a_0 + a_1 P(k) + a_2 T_{CG}(k) + \\ &+ a_3 \%\mathrm{CO}(k) + a_4 \%\mathrm{CO}_2(k) + a_5 lh(k) + a_6 V_{O_2}(k) \end{aligned} \tag{9}$$

In Table 2. the results of variant a) are presented.

Table 2. **Relative deviations prediction model for variant a)**
Tablica 2. **Model predviđanja relativnog odstupanja za varijantu a)**

Relative deviations [%]										
* M.	**58246**	**58247**	**58249**	**58250**	**58251**	**58253**	**58254**	**58255**	**58257**	** Av.
% C	2.7	47.6	12.2	26.5	10.7	11.5	165	22.2	212	56.7
T_{bath}	0.009	1.470	0.012	0.091	0.120	0.410	2.060	0.150	0.830	0.572

* Melting, ** Average

b) Prediction model for carbon content and bath temperature based on the content of CO, CO_2, and control variables.

$$\begin{aligned} \%\mathrm{C}(k+1) &= a_0 + a_1 \%\mathrm{CO}(k) + \\ &+ a_2 \%\mathrm{CO}_2(k) + a_3 lh(k) + a_4 V_{O_2}(k) \end{aligned} \tag{10}$$

$$\begin{aligned} \%T(k+1) &= a_0 + a_1 \%CO(k) + \\ &+ a_2 \%CO_2(k) + a_3 lh(k) + a_4 V_{O_2}(k) \end{aligned} \tag{11}$$

In Table 3. the results of variant b) are presented.

Table 3. **Relative deviations prediction model for variant b)**
Tablica 3. **Model predviđanja relativnog odstupanja za varijantu b)**

Relative deviations [%]										
* M.	**58246**	**58247**	**58249**	**58250**	**58251**	**58253**	**58254**	**58255**	**58257**	** Av.
% C	11.6	114	12.2	300	10.7	5.3	26.9	269	92.6	93.6
T_{bath}	0.138	1.200	0.011	1.420	0.120	0.470	0.270	1.090	0.690	0.606

* Melting, ** Average

c) Prediction model for bath temperature based on the content of CO, CO_2, temperature of converter gas, and control variables.

$$\begin{aligned} \%T(k+1) &= a_0 + a_1 \%\mathrm{CO}(k) + a_2 \%\mathrm{CO}_2(k) + \\ &+ a_3 \left(\frac{T_{CG}(k)}{100} \right)^4 + a_4 lh(k) + a_5 V_{O_2}(k) \end{aligned} \tag{12}$$

In Table 4. the results of variant c) are presented.

Table 4. **Relative deviations prediction model for variant c)**
Tablica 4. **Model predviđanja relativnog odstupanja za varijantu c)**

* M.	58246	58247	58249	58250	58251	58253	58254	58255	58257	** Av.
T_{bath}	0.810	1.170	0.007	0.660	0.120	0.240	0.156	0.040	0.280	0.306

Relative deviations [%]; * Melting, ** Average

Correction model for prediction of carbon

From the results of simulations of individual variants of the basic prediction model it can be seen, that the achieved deviations of carbon were considerably high. This led us to set up a correction model (13). The coefficients of the correction model were determined by using the least squares method and for the variables of the model we chose some static variables of the malleableazing process:

- the weight of pig iron;
- the weigh of scrap;
- the activity of oxygen in steel;
- the weight of lime;
- the temperature of pig iron;
- the content of carbon in pig iron.

$$\%C^{correction} = b_0 + b_1 T_{ri} + b_2 W_{ri} + + b_3 W_{lime} + b_4 W_{scrap} + b_5 A_{O_2} \tag{13}$$

where

b_0 is a parameter of the correction model,
W_{ri} is the weight of pig iron,
W_{lime} is the weight of lime,
W_{scrap} is weight of scrap,
A_{O_2} is the activity of oxygen in steel.

Table 5. **Relative deviations prediction model contents of carbon without and with correction model**
Tablica 5. **Model predviđanja relativnog odstupanja sadržaja ugljika bez korigiranja modela i s korigiranjem modela**

* M.	58246	58247	58249	58250	58251	58253	58254	58255	58257	** Av.
W***	11.6	114	12.2	300	10.7	5.3	26.9	296	92.6	93.6
With	9.8	42.3	1.1	1.6	10.7	8.6	38.7	94	4.7	23.5

Relative deviations [%]; * Melting, ** Average, ***Without

The resultant prediction model had the following form:

$$\%C^{result} = \%C^{basic} + \%C^{correction} \tag{14}$$

The resulting prediction model variant c) with correction model for carbon is in Table 5..

Optimization of parameters a_i of the basic prediction model by minimizing total deviation

We tried to minimize the total deviation of carbon content, which was given as the sum of deviations for individual melts. This task was transformed into the task of optimizing multidimensional tasks for which we chose the gradient method (15). The optimized vector in our case represents the vector of regression parameters a_i, and the function, which we will minimize, represents the total deviation [4].

$$\boldsymbol{a}^{i+1} = \boldsymbol{a}^{i} - h \cdot grad\, f\left(\boldsymbol{a}^{i}\right) \tag{15}$$

where

$\boldsymbol{a}^{i+1}$ is the vector regression parameters in next step,
$\boldsymbol{a}^{i}$ is the vector regression parameters in previous step,
$grad\, f(\boldsymbol{a}^{i})$ is the gradient,
h is the method step.

In this manner we eventually succeeded to reduce the total deviation of carbon content in the basic prediction model about 751 %.

CONCLUSION

In this paper we have tried to bring forward the advantages of predicting some non-measurable or hardly measurable variables not only in the converter process. Several variants and methods of putting the prediction model together are dealt with here. Each one of them has its advantages and disadvantages. The lowest average deviation for the prediction of carbon content was achieved with the prediction step size $\Delta t = 4$s. The prediction model is able to predict the carbon content with the deviation of 20 - 25 % and bath temperature 0.3 - 0.5 %.

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